Multi-Domain Sentiment Classification

TBD

Abstract

Introduction

Sentiment classification is a fundamental problem in sentiment analysis and also a hot topic in natural language processing. Recent work shows that by using neural network based supervised machine learning techniques, such as CNN and RNN, satisfying results can be achieved (Kim 2014; Socher et al. 2013; Graves and Schmidhuber 2005).

However, sentiment classification is widely accepted as a highly domain-dependent problem, because different words are used to express emotions in different domains. In some cases, even the same word may convey opposite sentiment in different domain. For example, "easy" is usually a positive word in *Electronics* domain, such like *"the computer is easy to use"*, while it may express negative sentiment in *DVD* domain, such like *"the ending is easy to guess"*. Therefore, a sentiment classifier for a specific domain may not perform well in other domains. Based on this observation, some domain-specific models have come up (Pang, Lee, and Vaithyanathan 2002; Chen et al. 2010).

A domain-specific model may have good performance when labeled data are sufficient. In practice, large scale of labeled data for some domains are hard to get and manually annotate data is time-consuming. So a useful idea is to utilize data from all domain to extract features that can improve domain-specific classifiers. A trivial method is to merge all data to train a general classifier, neglecting the domain information. There are also recent work to make domain as supplementary information to improve performance of the general classifier (Yuan et al. 2018), or construct information-sharing architecture to share information between each domain-specific classifiers (Liu, Qiu, and Huang 2016; Wu, Yuan, and Huang 2017).

TODO: INTRODUCING OUR WORK

Related work

Multi-Domain Sentiment Classification Sentiment classification is considered a domain-dependent problem. Recent work shows that domain-specific models have good performance (Pang, Lee, and Vaithyanathan 2002; Chen et al. 2010). For example, (Pang, Lee, and Vaithyanathan 2002) built sentiment classifier for movie reviews by using Naive Bayes, SVM and maximum entropy classification. (Chen et al. 2010) used opinion scoring models to extract opinionists' standpoints in political area.

Using transfer learning to adapt a certain domain that lacking labeled data, also known as **Domain Adaption**, is a popular method. There are two main approaches to apply transfer learning. One is to extract domain-independent features to build a generalized model for all domain (Blitzer, Dredze, and Pereira 2007; Pan et al. 2011). Another is to distinguish domain-dependent features to improve cross-domain classification (Bollegala, Weir, and Carroll 2011; Li et al. 2012). Our work combine both domain dependent and independent features to improve performance.

Multi-Task Learning Multi-task learning learns multiple tasks simultaneously in order to extract general features among each task. (Liu, Qiu, and Huang 2016) used a shared LSTM layer to learn common knowledge thus domain-specifics layers could use this knowledge to enhance their ability. (Wu, Yuan, and Huang 2017) combine general and domain-specific knowledge by calculating domain similarity and using regularization.

Attention Mechanism

Semi-Supervised Sentiment Classification

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